

*LCLUC SARI International Regional  
Science Meeting in SSEA  
Chiang Mai, Thailand  
July 17-19, 2017*

# Improving the Satellite Derived Forest Cover Dynamics in South and Southeast Asia

Atul Jain\*

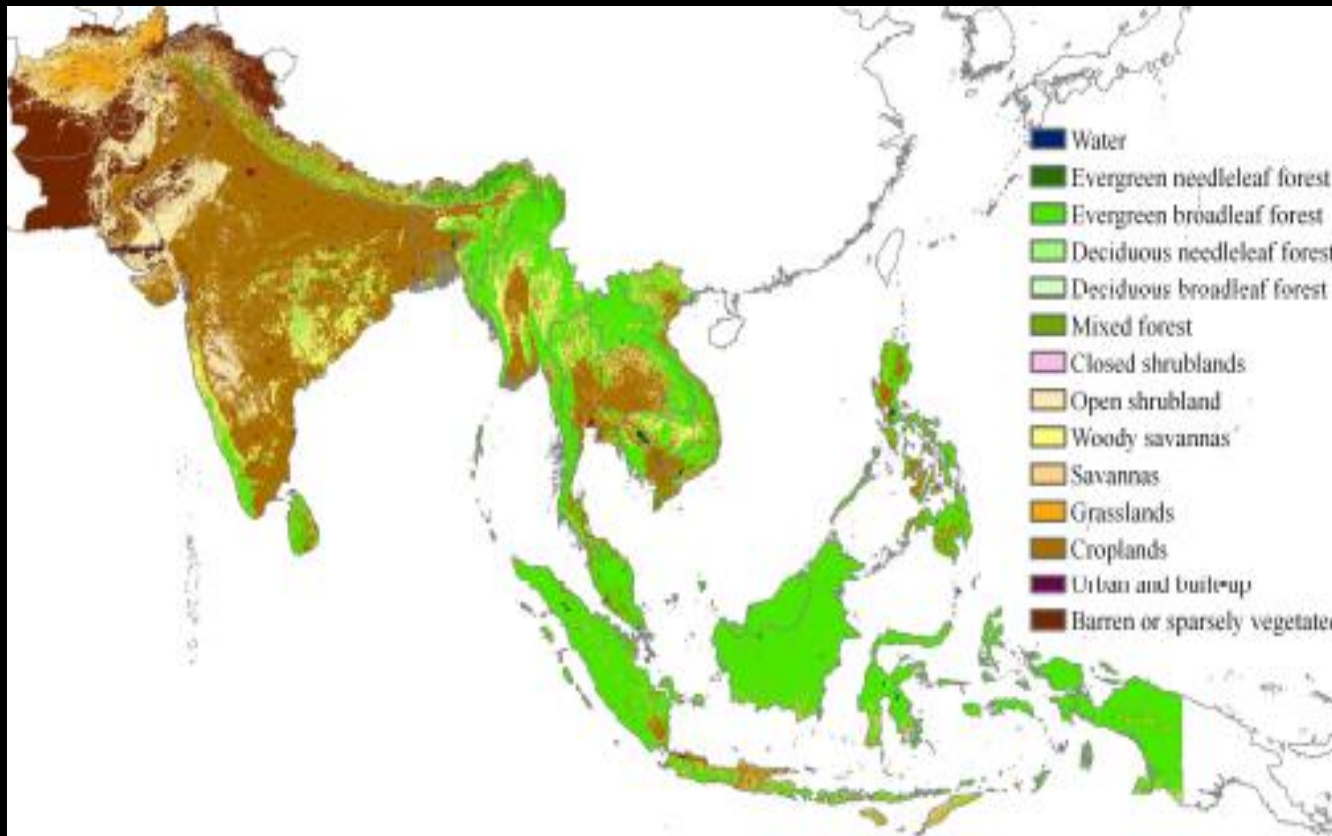
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## Acknowledgements

Hammad Gilani and Regional and US CO-Is & Collaborators  
NASA LCLUC Program, University of Illinois, UC

# SSEA Region



*LCLUC  
distribution  
in the study  
region*

- Covers about 16% of earth's land surface
- Characterized by a long history of LCLUC activities
- The home for over 50% of the world's population
- *Understand the LCLUC dynamics and drivers*

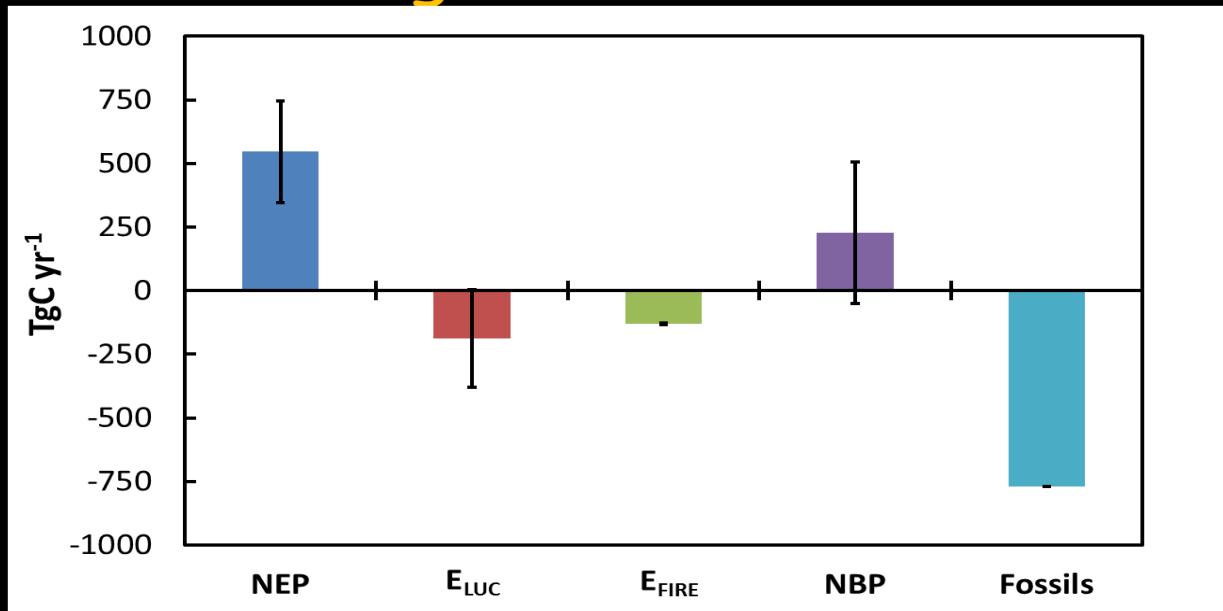
# Background

- Three principal objectives
  - *To understand the major LCLUC transition activities in the study region.*
  - *To advance our understanding of the causes of LCLUC.*
  - *To improve our understanding of the historical effects of LCLUC dynamics on the quantities and pathways of terrestrial carbon and nitrogen fluxes.*

# The terrestrial carbon budget of South and Southeast Asia

Matthew Cervarich<sup>1</sup>, Shijie Shu<sup>1</sup>, Atul K Jain<sup>1,15</sup>, Almut Arneth<sup>2</sup>, Josep Canadell<sup>3</sup>, Pierre Friedlingstein<sup>4</sup>, Richard A Houghton<sup>5</sup>, Etsushi Kato<sup>6</sup>, Charles Koven<sup>7</sup>, Prabir Patra<sup>8</sup>, Ben Poulter<sup>9</sup>, Stephen Sitch<sup>10</sup>, Beni Stocker<sup>11</sup>, Nicolas Viovy<sup>12</sup>, Andy Wiltshire<sup>13</sup> and Ning Zeng<sup>14</sup>

## Mean Carbon Fluxes SSEA Average for 2000-2013



\*Positive values are the land sink of carbon

Cervarich et al. (ERL, 2016)

# Global Carbon Budget 2016

Corinne Le Quéré<sup>1</sup>, Robbie M. Andrew<sup>2</sup>, Josep G. Canadell<sup>3</sup>, Stephen Sitch<sup>4</sup>, Jan Ivar Korsbakken<sup>2</sup>, Glen P. Peters<sup>2</sup>, Andrew C. Manning<sup>5</sup>, Thomas A. Boden<sup>6</sup>, Pieter P. Tans<sup>7</sup>, Richard A. Houghton<sup>8</sup>,

Ralph F. Keeling<sup>9</sup>, Sir

Laurent Bopp<sup>14</sup>, Fran

Christine Delire<sup>17</sup>, Scot

Judith Hauck<sup>22</sup>, Vanes

Etsushi Kato<sup>26</sup>, Arne K

Sebastian Lienert<sup>31,32</sup>, I

Pedro M. S. Monteir

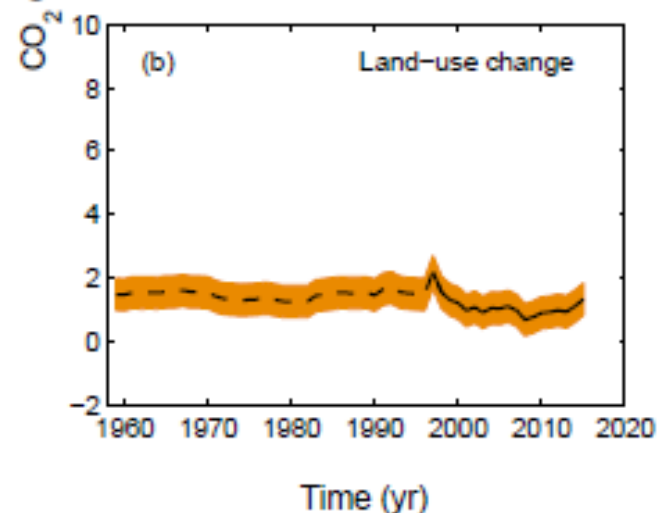
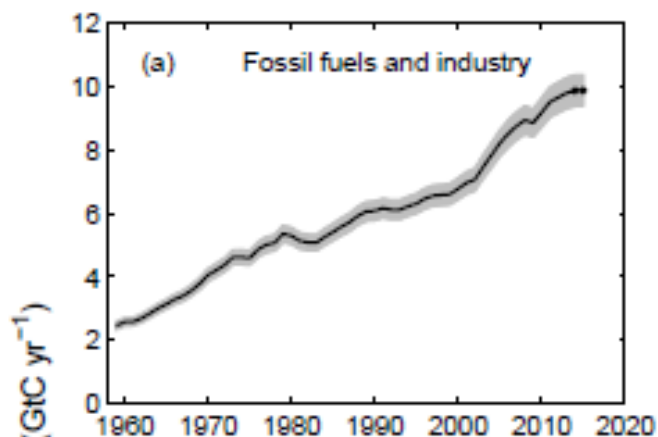
Kevin O'Brien<sup>39</sup>, Ar

Benjamin Poulter<sup>42,43</sup>, C

Roland Séférian<sup>17</sup>, Ingunn S

Hanqin Tian<sup>49</sup>, Bronte

Nicolas Viovy<sup>14</sup>,



thoni<sup>11</sup>, Leticia Barbero<sup>12,13</sup>,

pppe Ciais<sup>14</sup>, Kim Currie<sup>16</sup>,

nos Gkritzalis<sup>20</sup>, Ian Harris<sup>21</sup>,

n Goldewijk<sup>24</sup>, **Atul K. Jain**<sup>25</sup>,

e Lefèvre<sup>29</sup>, Andrew Lenton<sup>30</sup>,

colas Metzl<sup>29</sup>, Frank Millero<sup>35</sup>,

l<sup>28</sup>, Shin-ichiro Nakaoka<sup>38</sup>,

o Ono<sup>41</sup>, Denis Pierrot<sup>12,13</sup>,

e Schuster<sup>4</sup>, Jörg Schwinger<sup>46</sup>,

ie J. Sutton<sup>39,10</sup>, Taro Takahashi<sup>48</sup>,

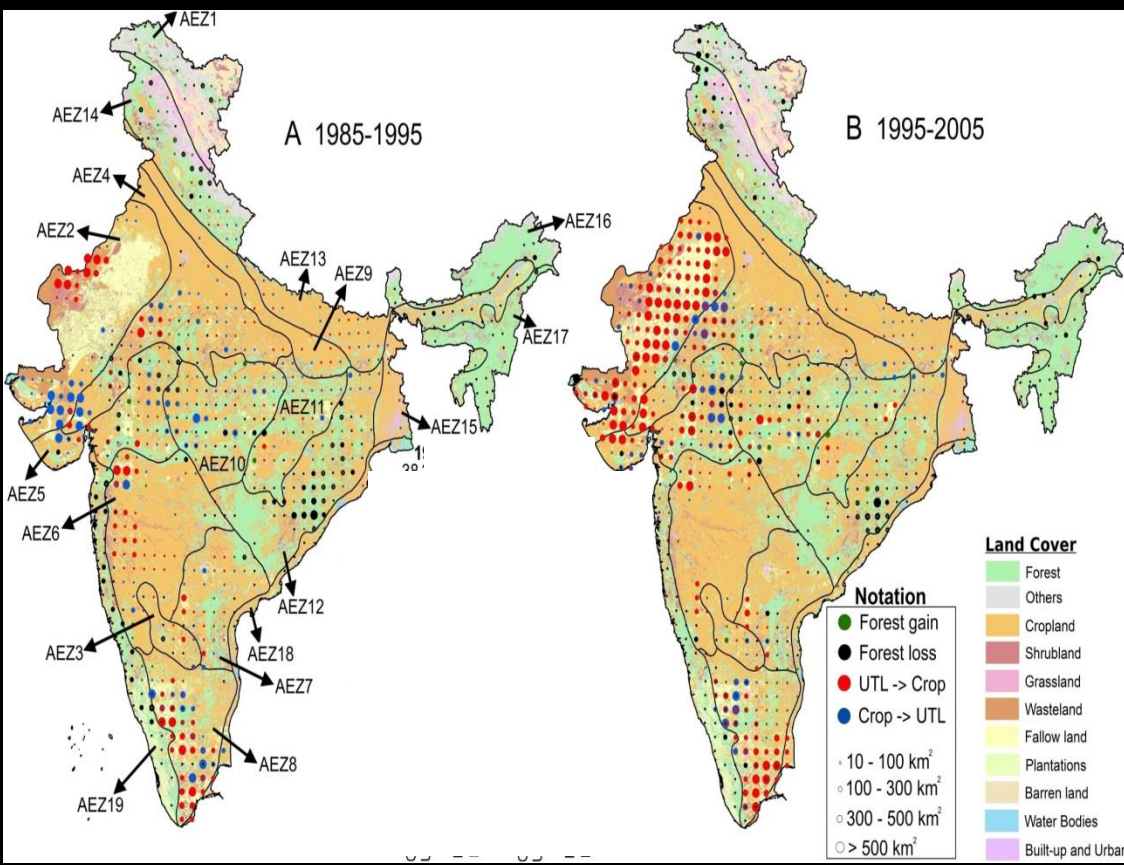
κ<sup>51</sup>, Guido R. van der Werf<sup>52</sup>,

54, and Sönke Zaehle<sup>44</sup>

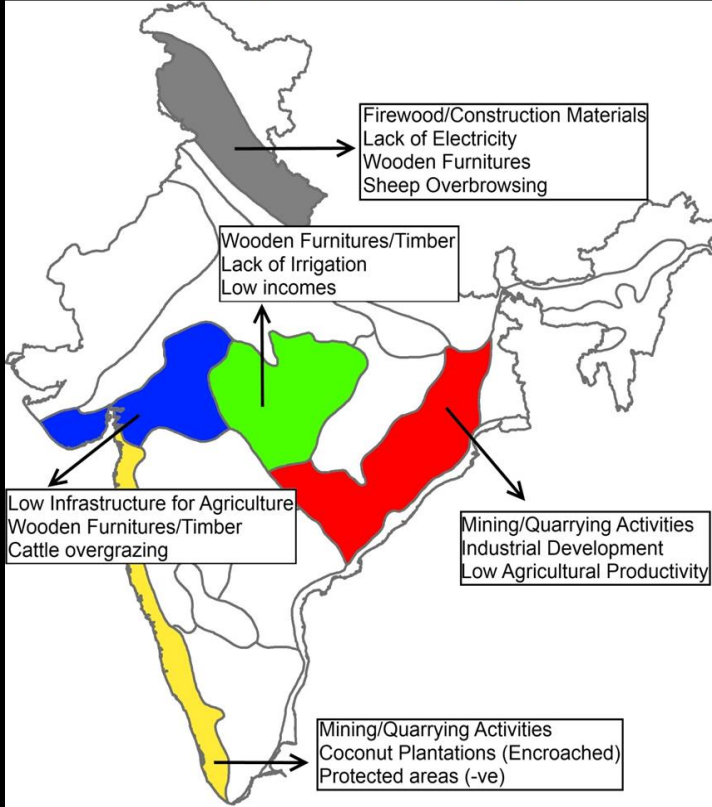
# Dynamics and determinants of land change in India: integrating satellite data with village socioeconomics

Reg Environ Change  
DOI 10.1007/s10113-016-1068-2

Prasanth Meiyappan<sup>1</sup> · Parth S. Roy<sup>2</sup> · Yeshu Sharma<sup>3</sup> · Reshma M. Ramachandran<sup>2</sup> · Pawan K. Joshi<sup>4</sup> · Ruth S. DeFries<sup>5</sup> · Atul K. Jain<sup>1</sup>



## Major findings



# Assessing uncertainties in land cover projections

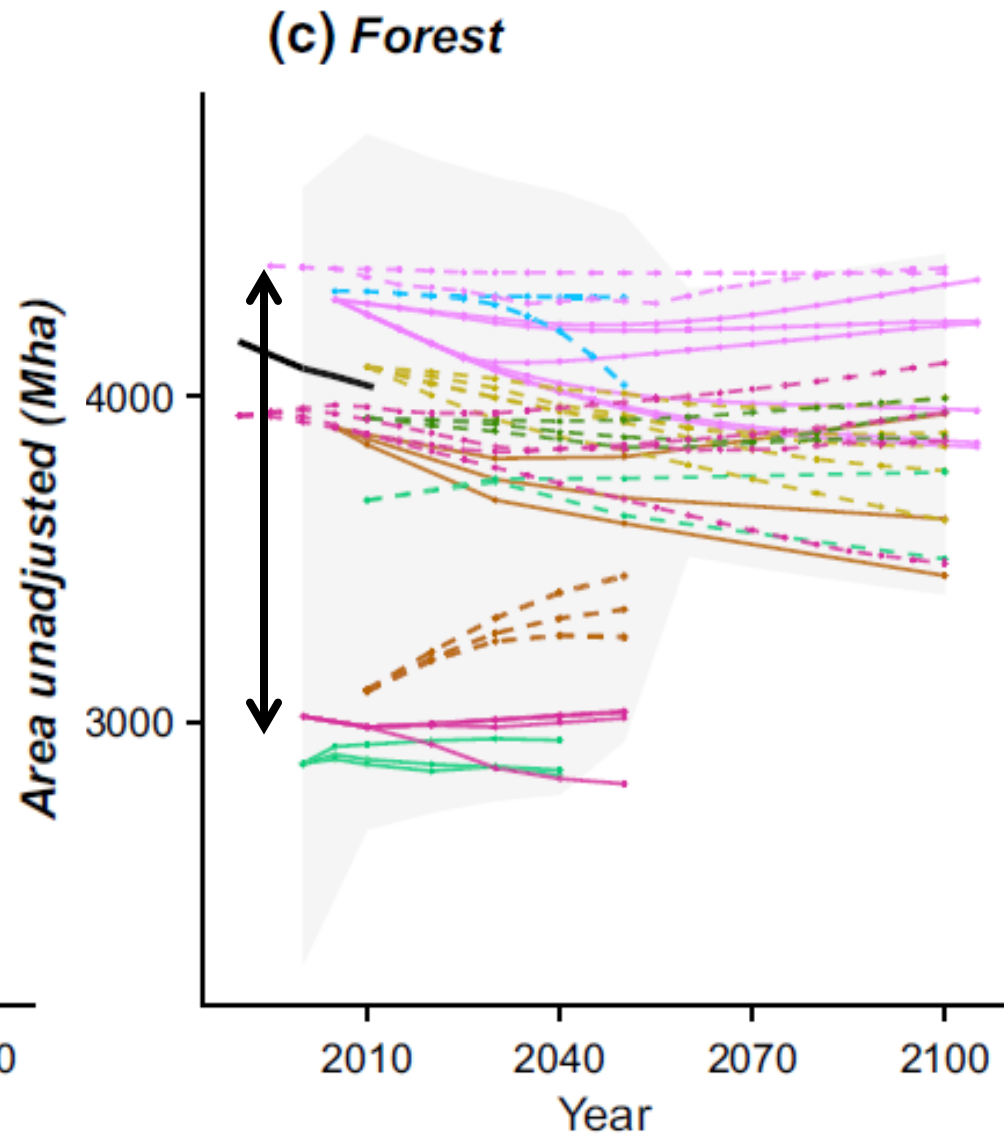
PETER ALEXANDER<sup>1,2</sup>, REINHARD PRESTELE<sup>3</sup>, PETER H. VERBURG<sup>3</sup>, ALMUT ARNETH<sup>4</sup>, CLAUDIA BARANZELLI<sup>5</sup>, FILIPE BATISTA E SILVA<sup>5</sup>, CALUM BROWN<sup>1</sup>, ADAM BUTLER<sup>6</sup>, KATHERINE CALVIN<sup>7</sup>, NICOLAS DENDONCKER<sup>8</sup>, JONATHAN C. DOELMAN<sup>9</sup>, ROBERT DUNFORD<sup>10,11</sup>, KERSTIN ENGSTRÖM<sup>12</sup>, DAVID EITELBERG<sup>3</sup>, SHINICHIRO FUJIMORI<sup>13</sup>, PAULA A. HARRISON<sup>11</sup>, TOMOKO HASEGAWA<sup>13</sup>, PETR HAVLIK<sup>14</sup>, SASCHA HOLZHAUER<sup>1</sup>, FLORIAN HUMPENÖDER<sup>15</sup>, CHRIS JACOBS-CRISIONI<sup>5</sup>, ATUL K. JAIN<sup>16</sup>, TAMÁS KRISZTIN<sup>14</sup>, PAGE KYLE<sup>7</sup>, CARLO LAVALLE<sup>5</sup>, TIM LENTON<sup>17</sup>, JIAYI LIU<sup>6</sup>, PRASANTH MEIYAPPAN<sup>16</sup>, ALEXANDER POPP<sup>15</sup>, TOM POWELL<sup>17</sup>, RONALD D. SANDS<sup>18</sup>, RÜDIGER SCHALDACH<sup>19</sup>, ELKE STEHFEST<sup>9</sup>, JEVGENIJS STEINBUKS<sup>20</sup>, ANDRZEJ TABEAU<sup>21</sup>, HANS VAN MEIJL<sup>21</sup>, MARSHALL A. WISE<sup>7</sup> and MARK D. A. ROUNSEVELL<sup>1</sup>

the differences attributed to the scenario variations. The results lead us to conclude that a higher degree of uncertainty exists in land use projections than currently included in climate or earth system projections. To account for land use uncertainty, it is recommended to use a diverse set of models and approaches when assessing the potential impacts of land cover change on future climate. Additionally, further work is needed to better understand the

# Assessing uncertainties in land cover projections

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UT ARNETH<sup>4</sup>,  
AM BUTLER<sup>6</sup>,  
N<sup>9</sup>,  
3,  
E<sup>7</sup>,  
I ALDACH<sup>19</sup>,  
AN MEIJL<sup>21</sup>,



the differences attributed to  
uncertainty exists in land use pro  
use uncertainty, it is recor  
impacts of land cover cha

degree of uncer-  
to account for land  
missing the potential  
er understand the



# Today's Talk

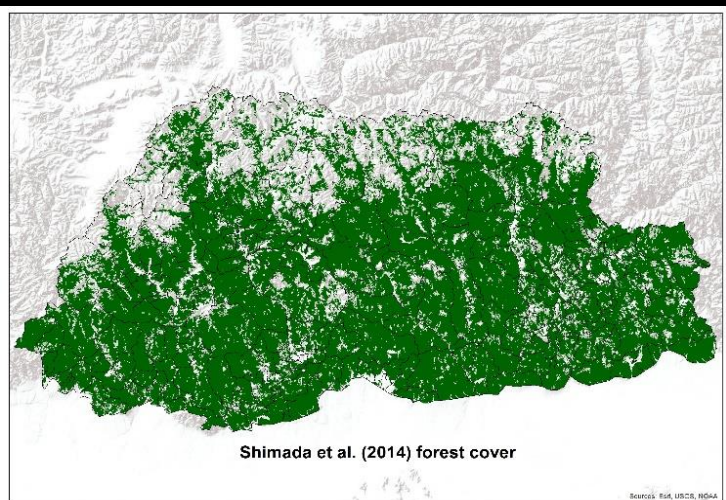
- Syntheses of existing satellite data for forest cover in SSEA
  - Global scale and country scale
- Understanding the causes of differences between different datasets
- Understanding the causes of agreements
- Improving the existing data - some thoughts

# Satellite Derived Forest Cover Datasets ( $\leq 30$ Spatial Resolution)

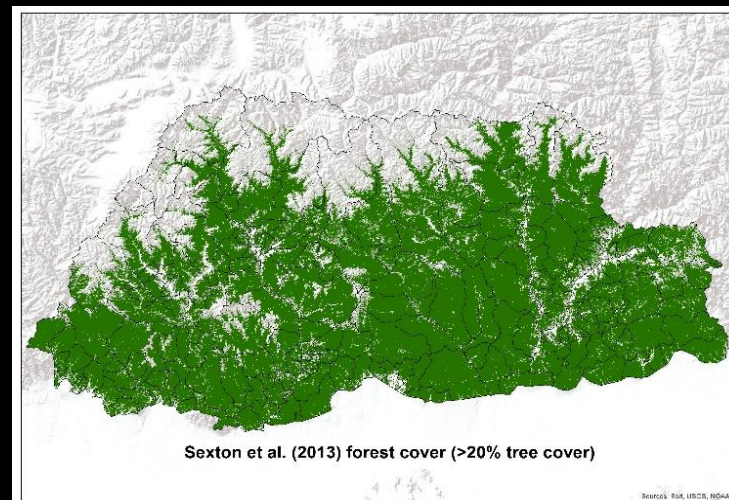
Data Source	Spatial Resolution (m)	Classification Algorithm	Forest Definition		Reference
			Tree Density (> %)	Tree Height (m)	
PALSAR	25	Decision Tree	10		Shimada et al. (2014)
Landsat, MODIS	30	Supervised classification (Decision Tree)	10	5	Sexton et al. (2013)
Landsat	30	Supervised classification	10	5	Hansen et al. (2013)
Landsat, HJ-1	30	POK-based method	10		*Chen et al. (2015)

\* Available only for Nepal and Bhutan

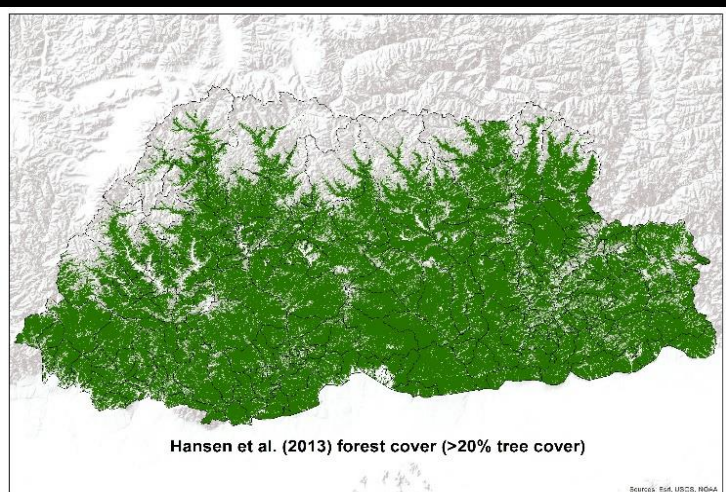
# Bhutan - Satellite Derived Forest Cover for 2010



18,367 km<sup>2</sup> (48%)

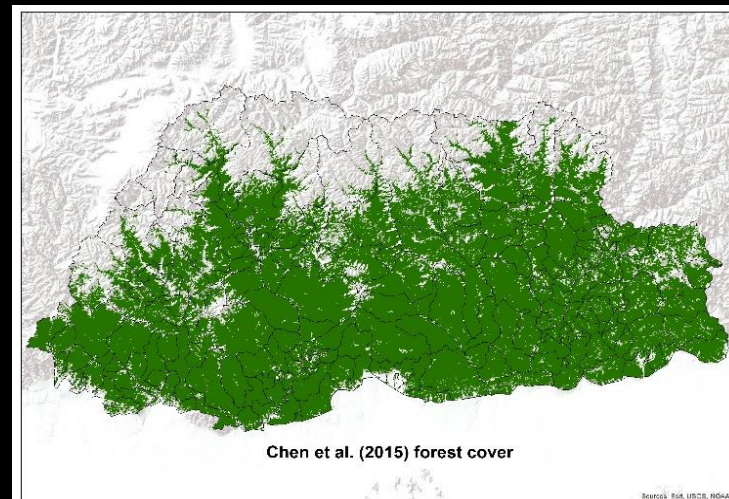


22,015 km<sup>2</sup> (57%)



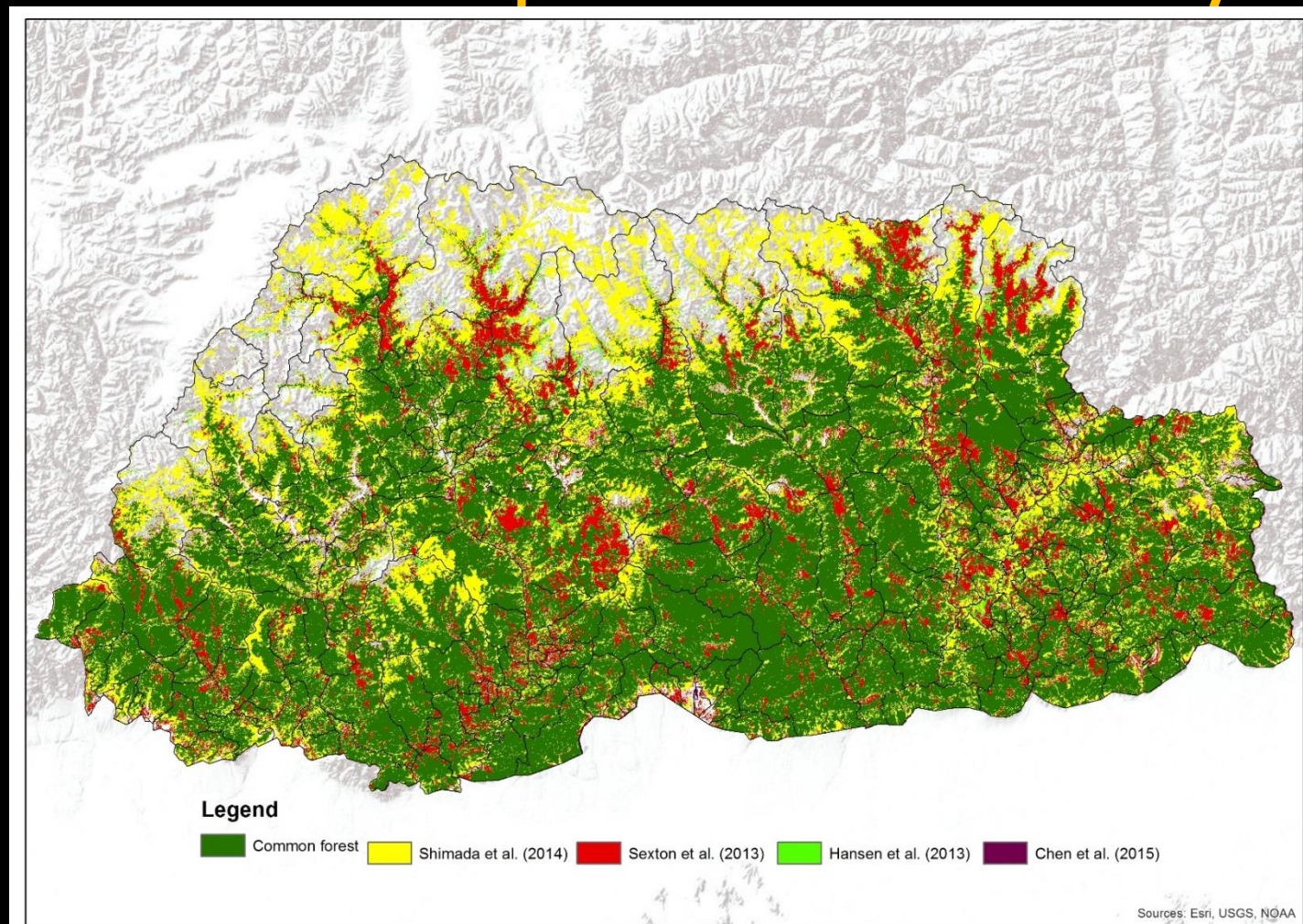
34,450 km<sup>2</sup> (90%)

Official forest area is 27,053 km<sup>2</sup> (70%) of the total land area of Bhutan (38,394 km<sup>2</sup>)



26,479 km<sup>2</sup> (70%)

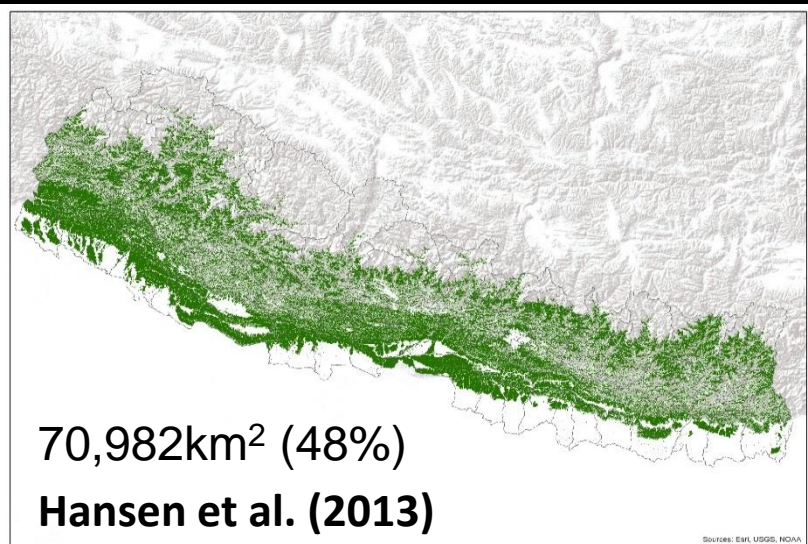
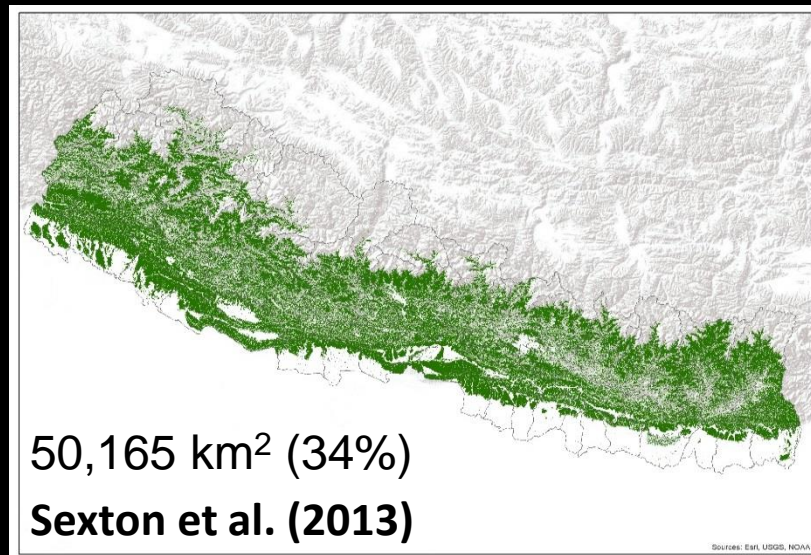
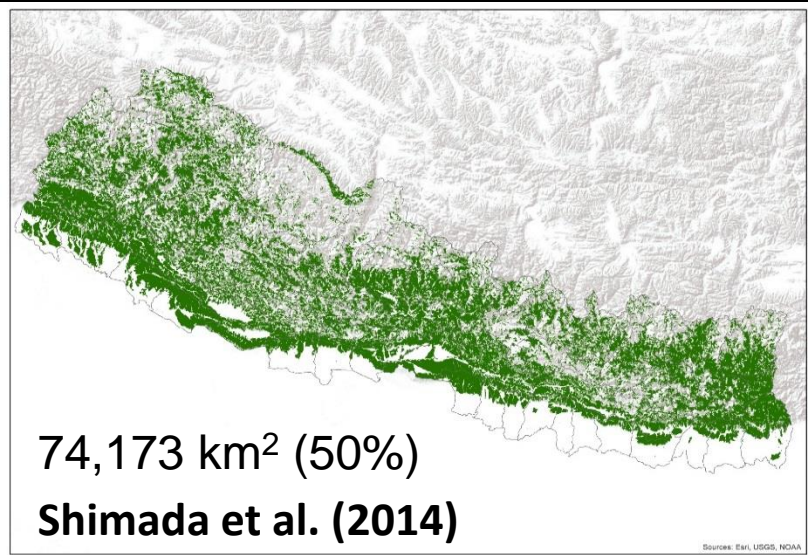
# Bhutan - Satellite Derived Forest Covers Spatial Consistency



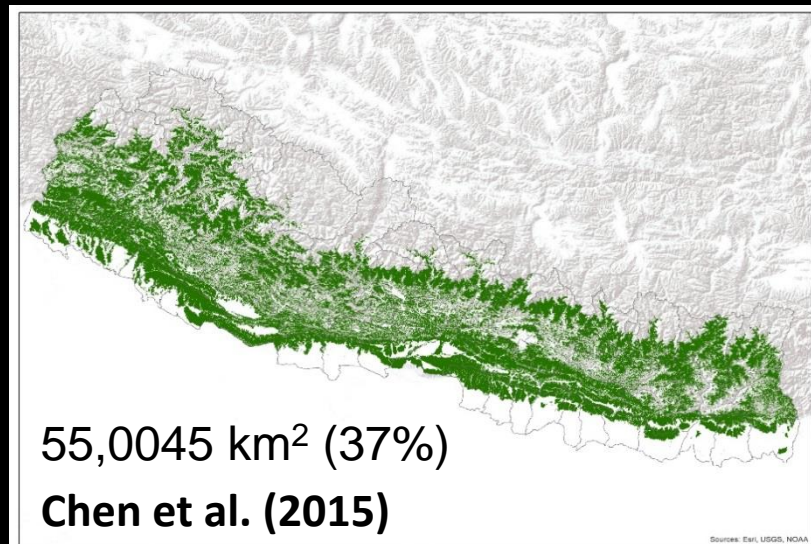
Common Forest area 11,884 km<sup>2</sup> (31%)

Gilani et al. (in preparation, 2017)

# Nepal - Satellite Derived Forest Cover for 2010

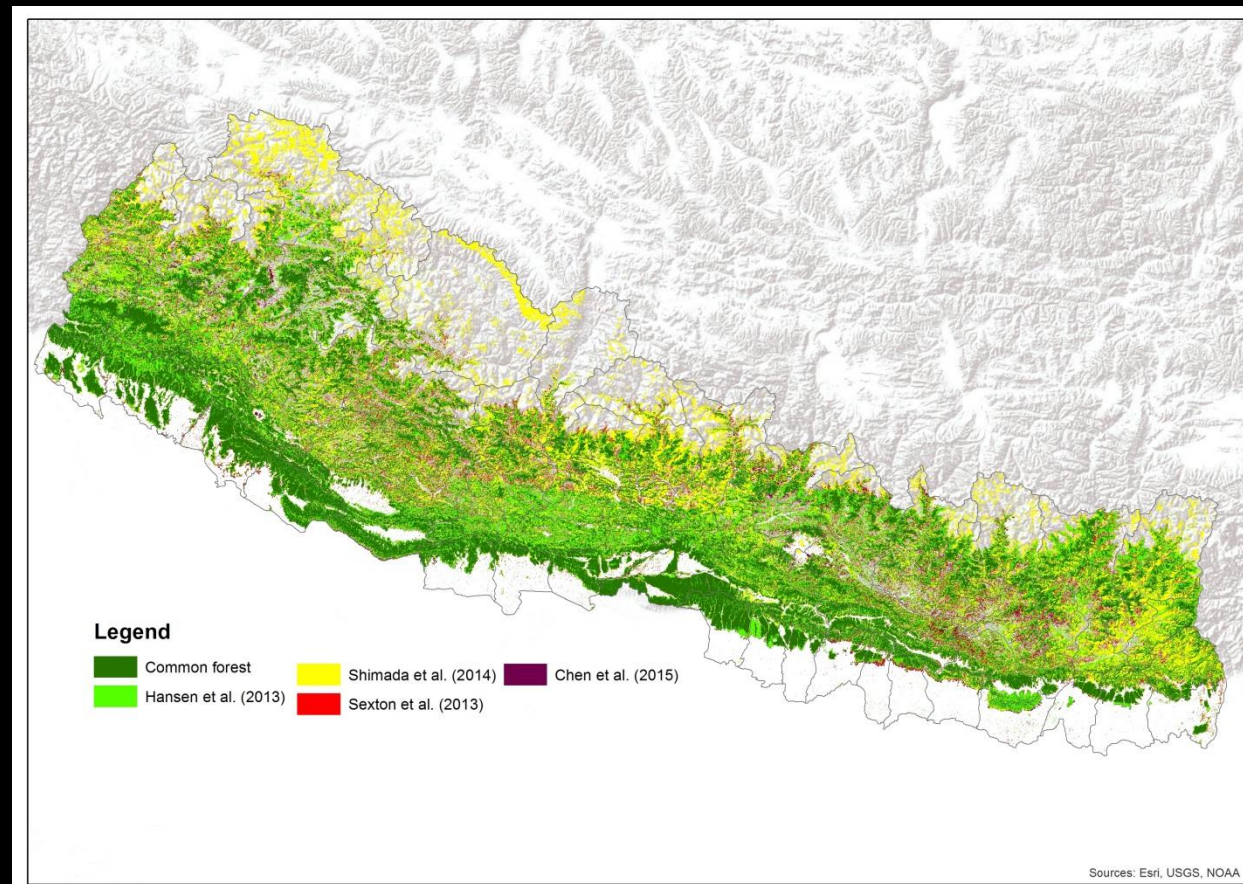


Official  
forest cover  
area is 40 %  
of the total  
land area of  
Nepal  
(147,181  
km<sup>2</sup>)



**Gilani et al. (in preparation, 2017)**

# Nepal - Satellite Derived Forest Covers Spatial Consistency

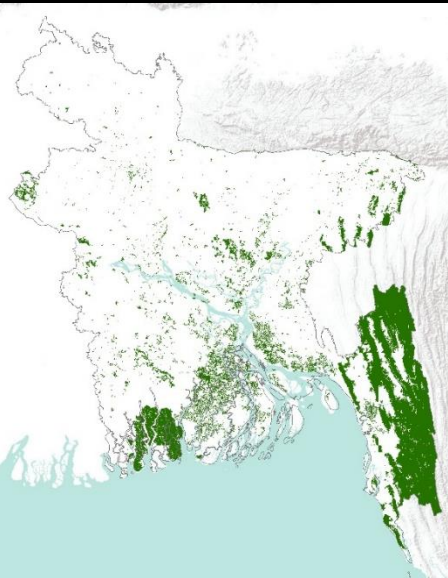


Common area: 26,261 Sq. km (18%)

Gilani et al. (in preparation, 2017)

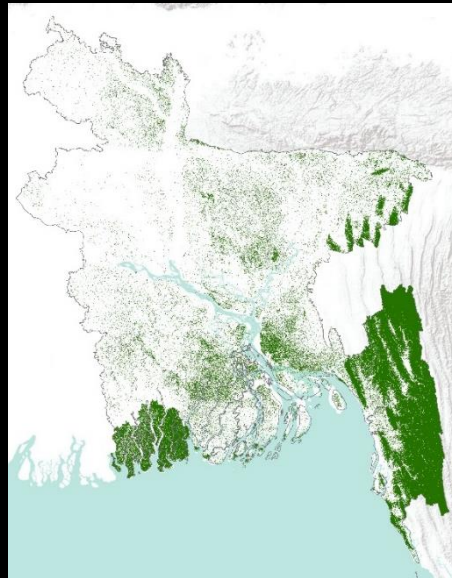
# Bangladesh - Satellite Derived Forest Cover for 2010

Shimada et al. (2014)



23,199 km<sup>2</sup> (16%)

Sexton et al. (2013)



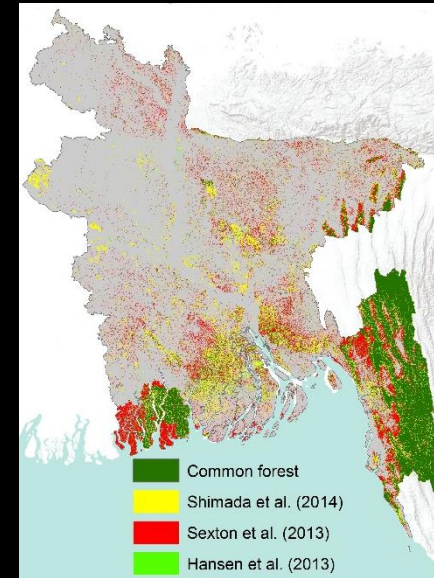
25,892 km<sup>2</sup> (18%)

Hansen et al. (2013)



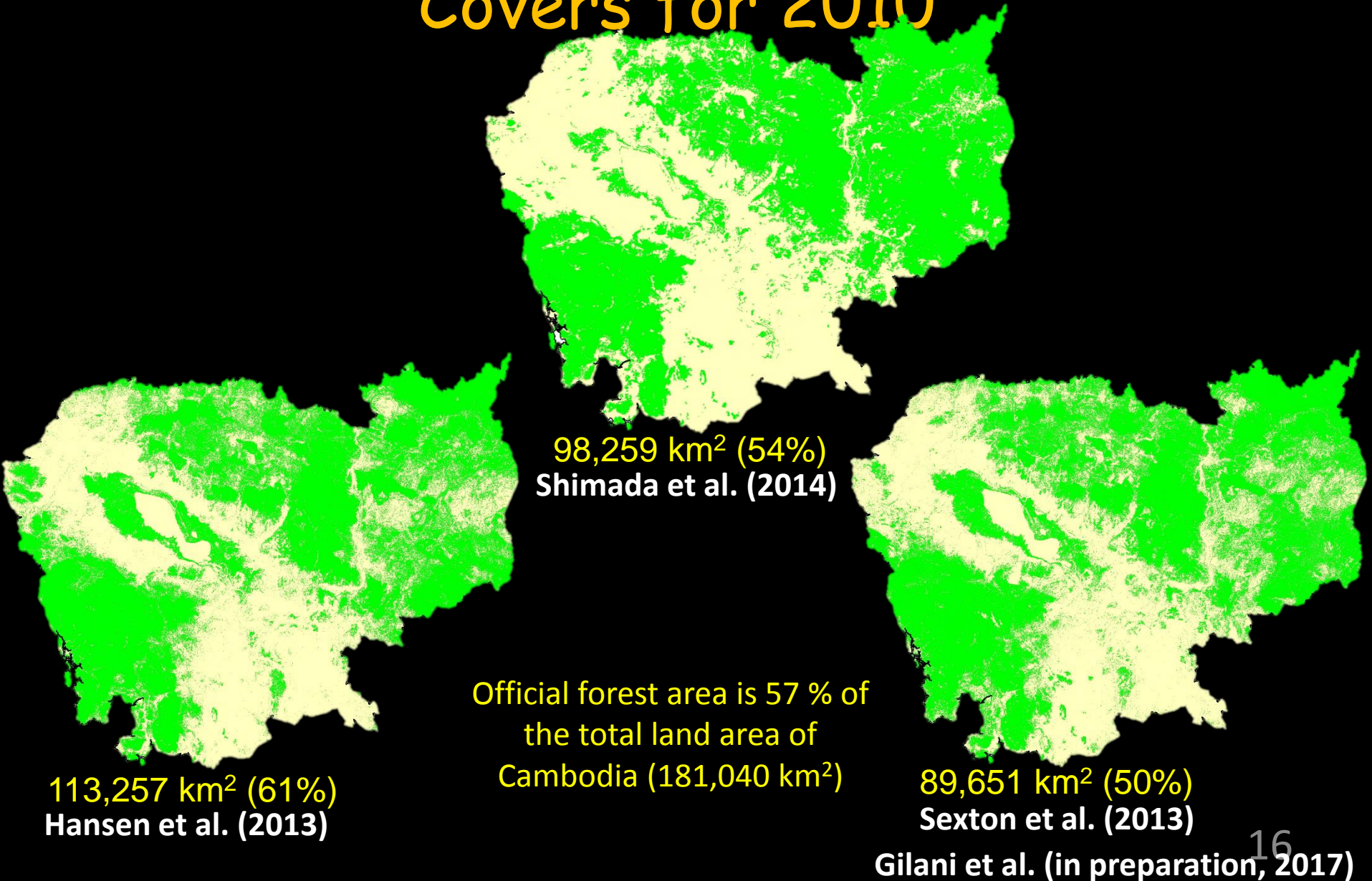
22,709 km<sup>2</sup> (15%)

Commonly classified



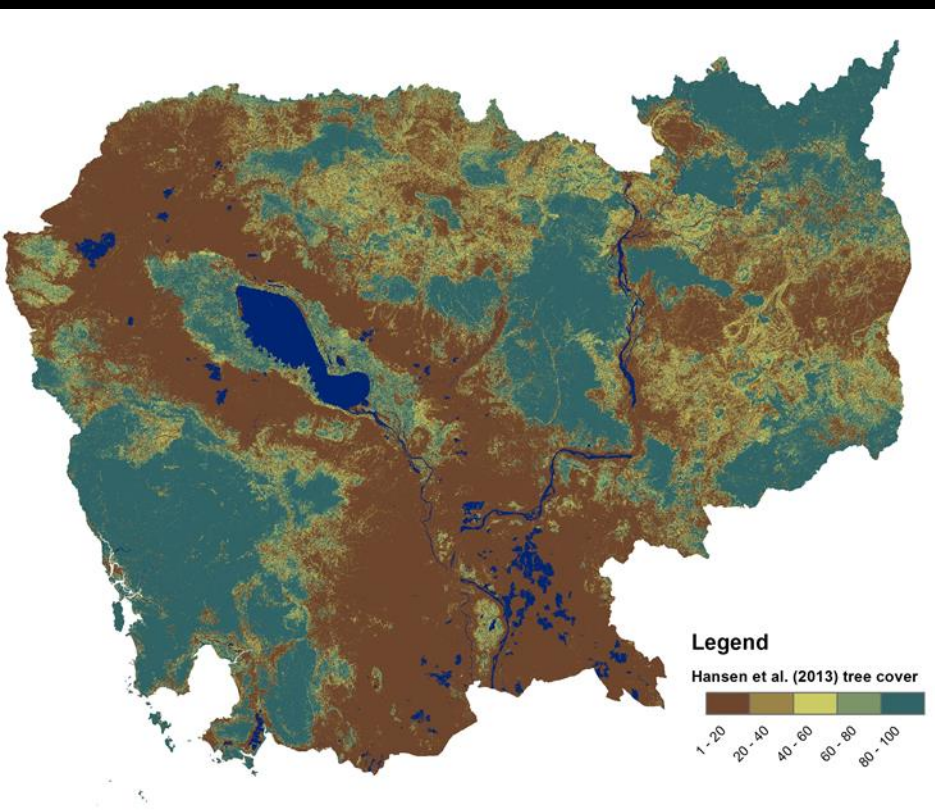
11,935 km<sup>2</sup> (8%)

# Cambodia - Satellite Derived Forest Covers for 2010

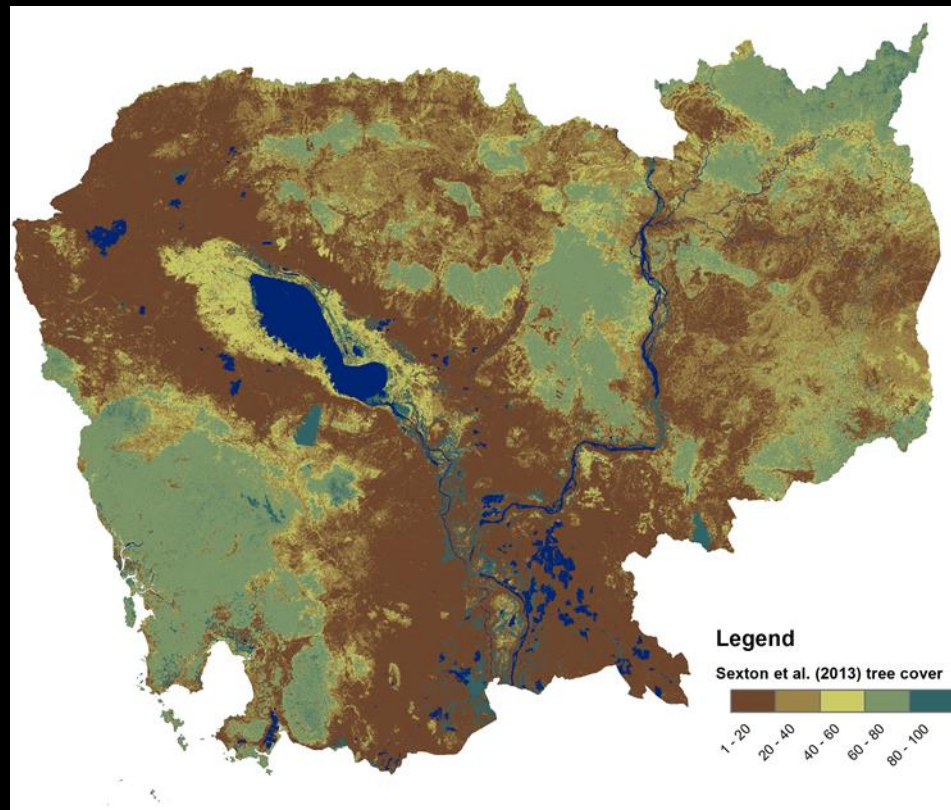




# Cambodia - Satellite Derived Tree Covers for circa 2010



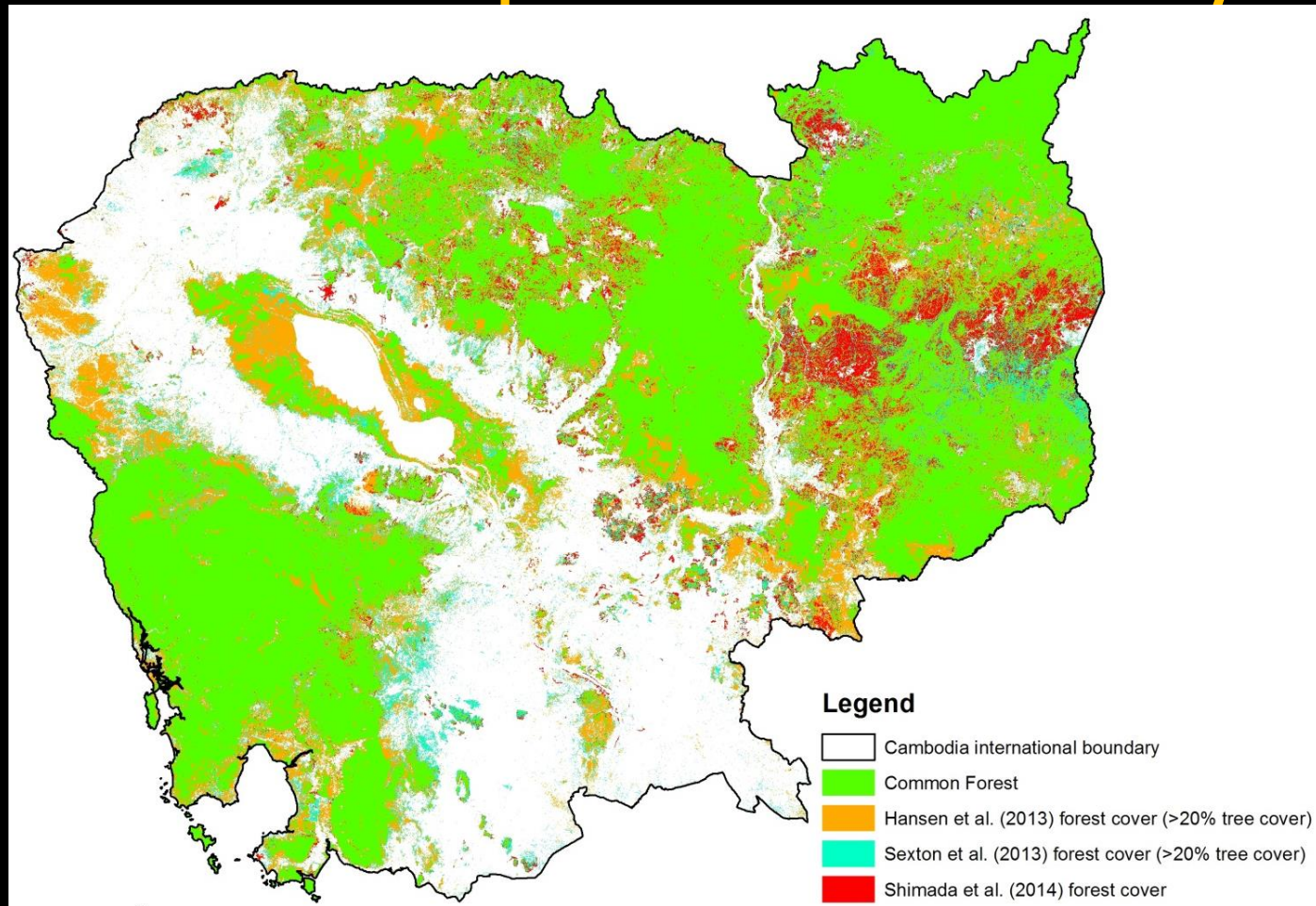
Hansen et al. (2013)



Sexton et al. (2013)

Gilani et al. (in preparation, 2017)

# Cambodia - Satellite Derived Forest Covers Spatial Consistency



Uncommon forest area is about 26% of the total land area  
(181,040 km<sup>2</sup>)

# Why are the Differences..

- Algorithms are trained based on limited ground data
- Forest definition varies
- Atmosphere and topographical effects are treated differently by the algorithms used
- Forest classification is mixed with other vegetation types;
  - Shrub and scrub lands mixed with forest class due to spectral response/signatures
- Limited ground data for the training and testing
- Post-processing (Smoothing filters, Minimum Mapping Units etc.)

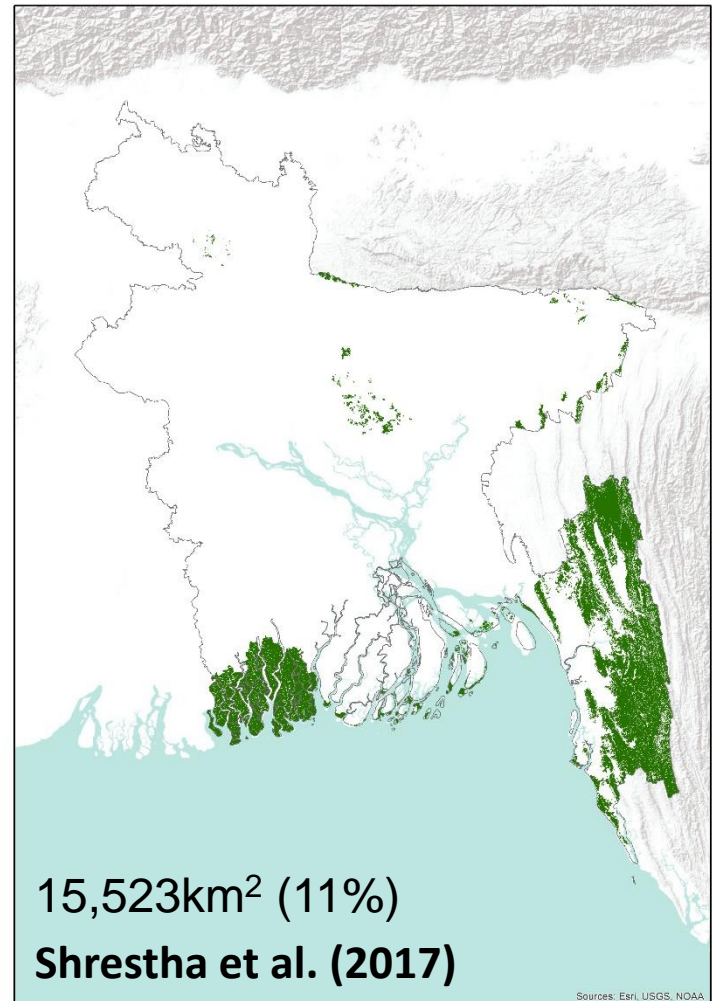
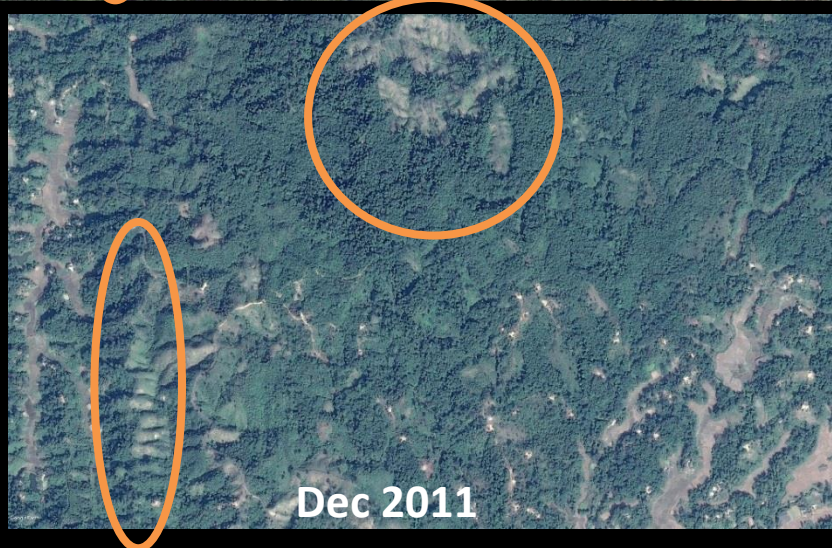
# Why are the Agreements..

- Dense patches of the forests are easily detected and mapped, because the same or similar optical remote sensing datasets are used
- Lower tree density classes (<60%) are matching

# Dynamics of LCLUC - Country Level Studies

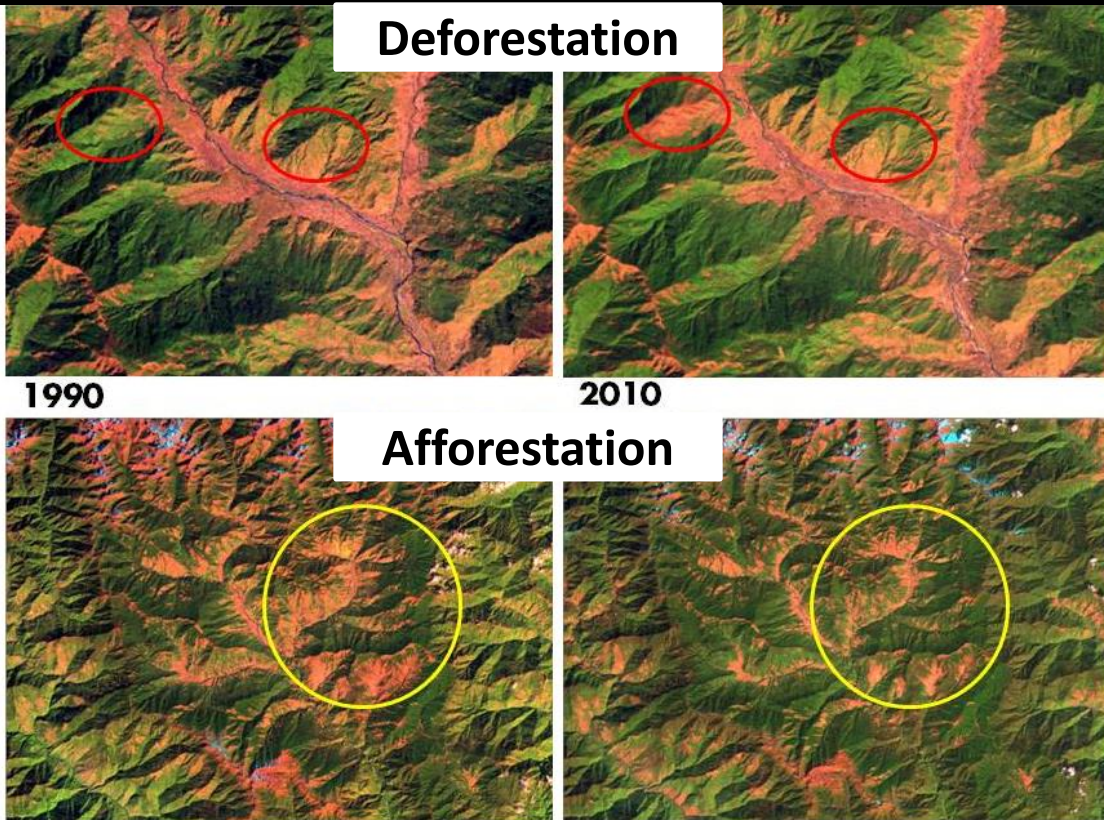
# Bangladesh - A Temporal Change Assessment and Forest Mapping

Lat. 23.399811°, Long. 92.018261°



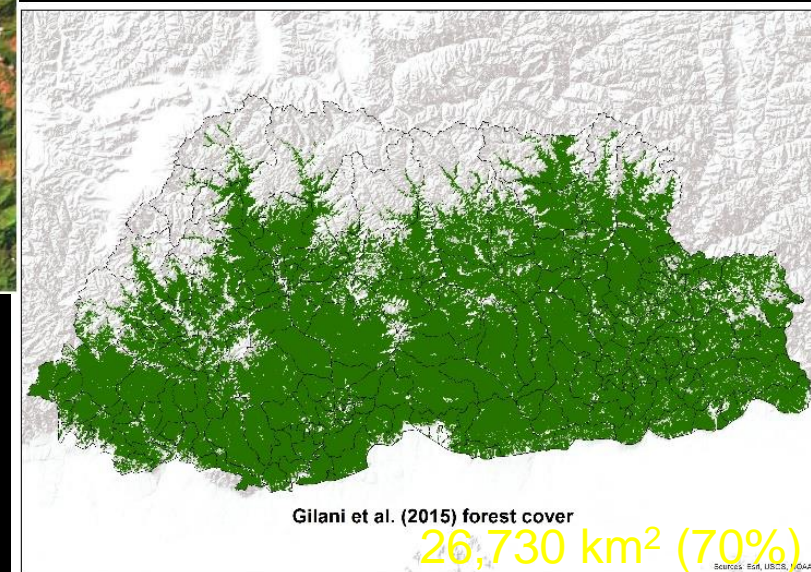
Selected reference points (Ground and Google Earth High Resolution Satellite Imagery - Validation

# Bhutan - A Temporal Change Assessment and Forest Mapping



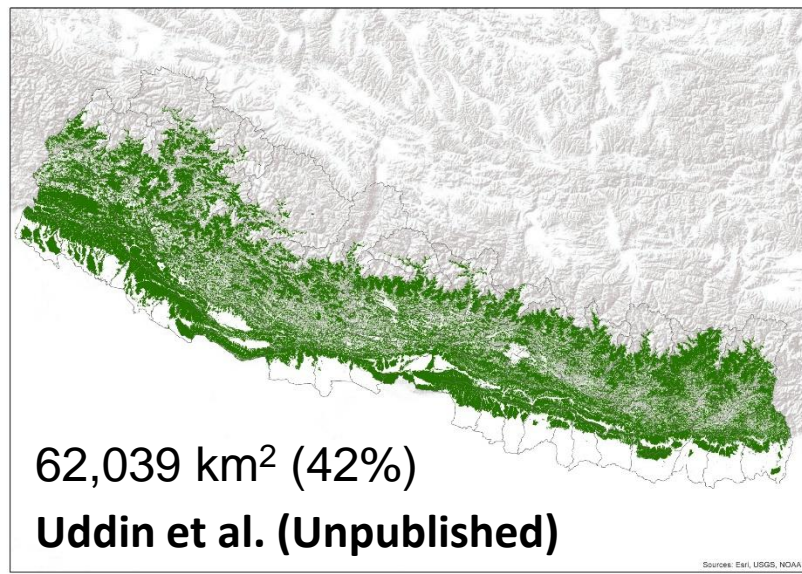
Time varying images were used to map forest cover changes

Forest cover and change maps were evaluated for the accuracy using Google Earth and ground based measurements

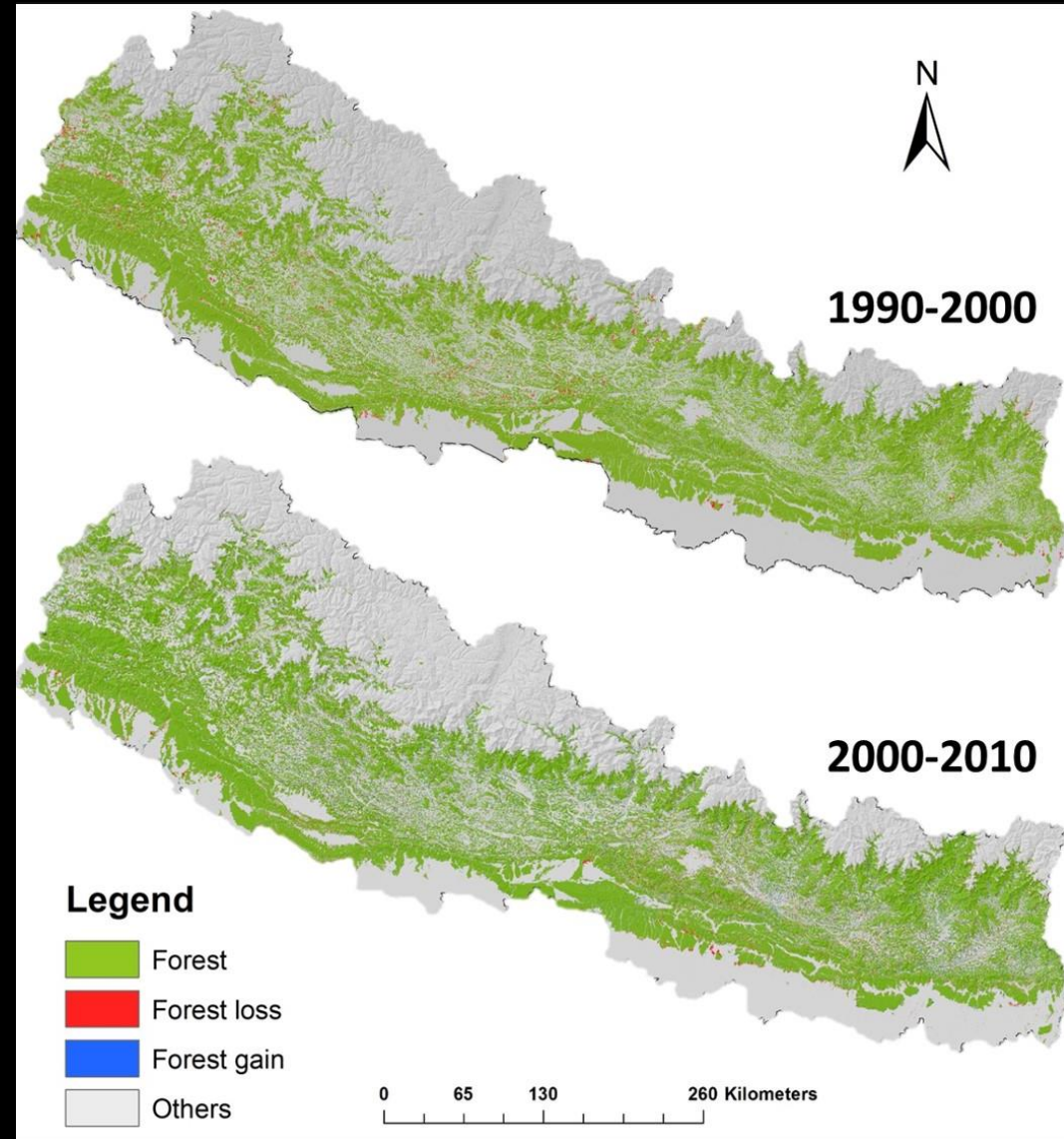
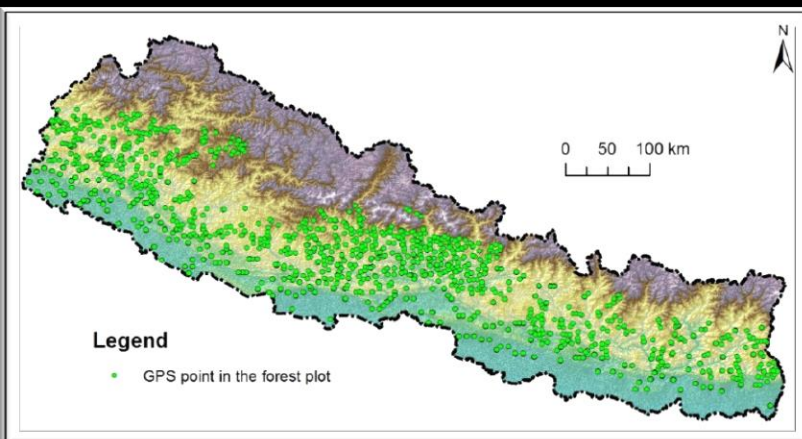


Gilani et al. (2015)

# Nepal - A Temporal Change Assessment and Forest Mapping



1,646 reference points for the accuracy assessment and validation of forest cover and forest cover change maps

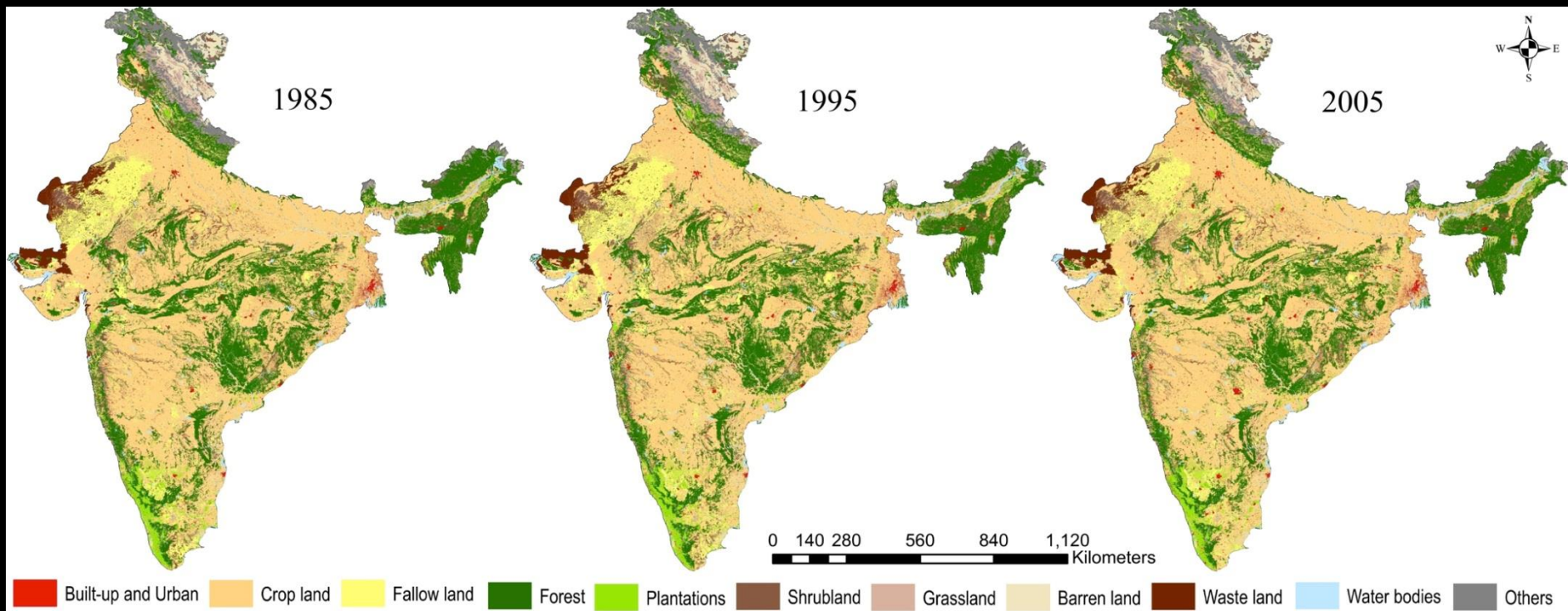


Gilani et al. (in preparation, 2017)<sup>4</sup>

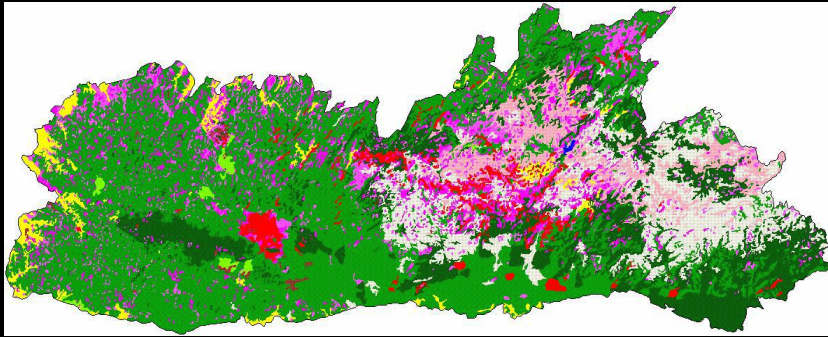


# Wall-to-wall Landsat Analysis for India

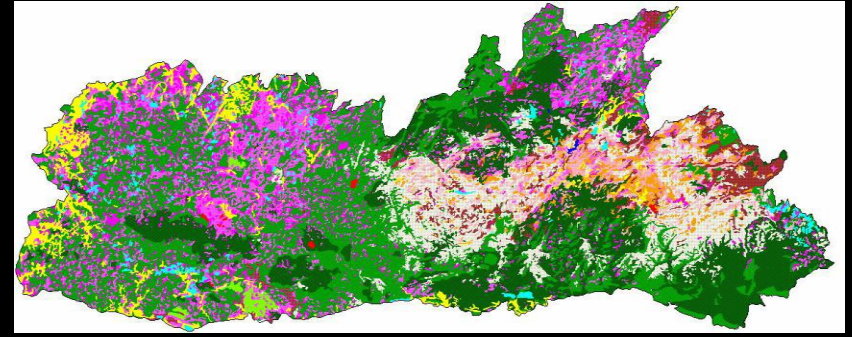
- Covers Longer Time Period: Decadal (1985-1995-2005)
- Uniform Classification Scheme: IGBP
- Patch to Patch Land Dynamics
- Field samples (>12000 points)



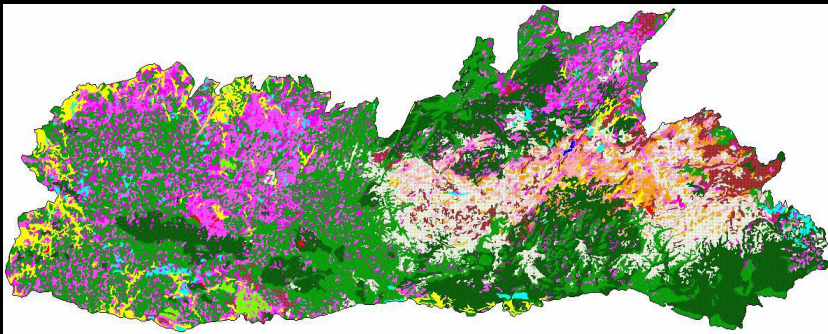
# Forest Dynamics in Meghalaya - Satellite Derived Vegetation Type Maps



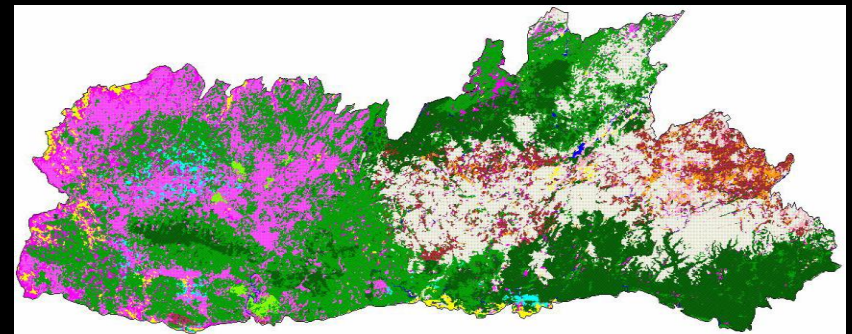
1980



1985



1995



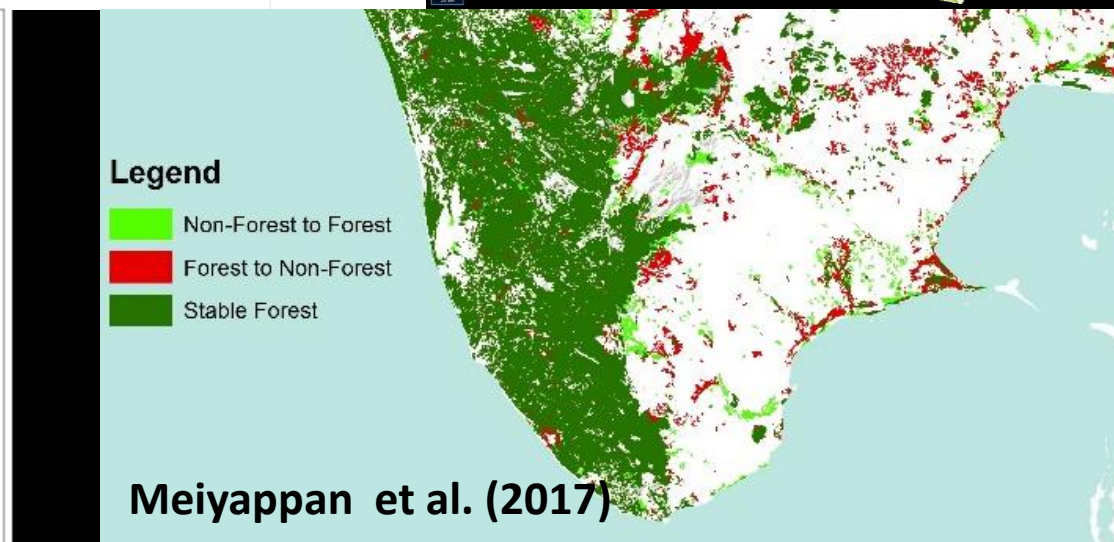
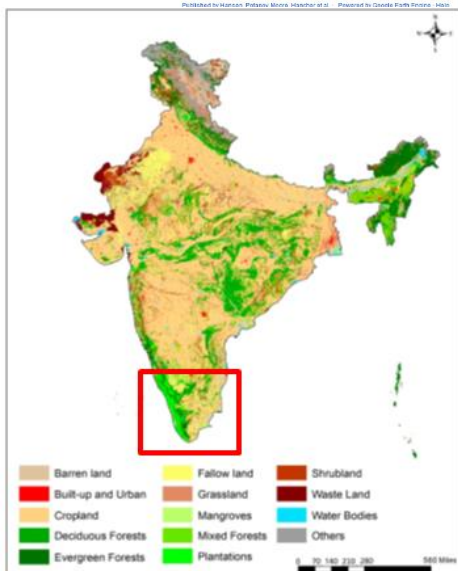
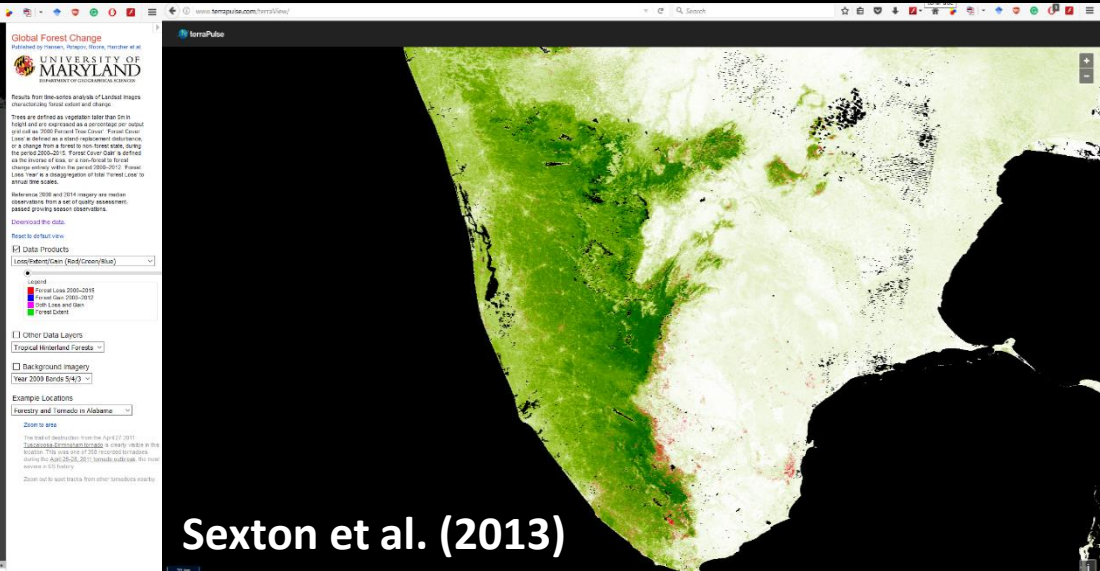
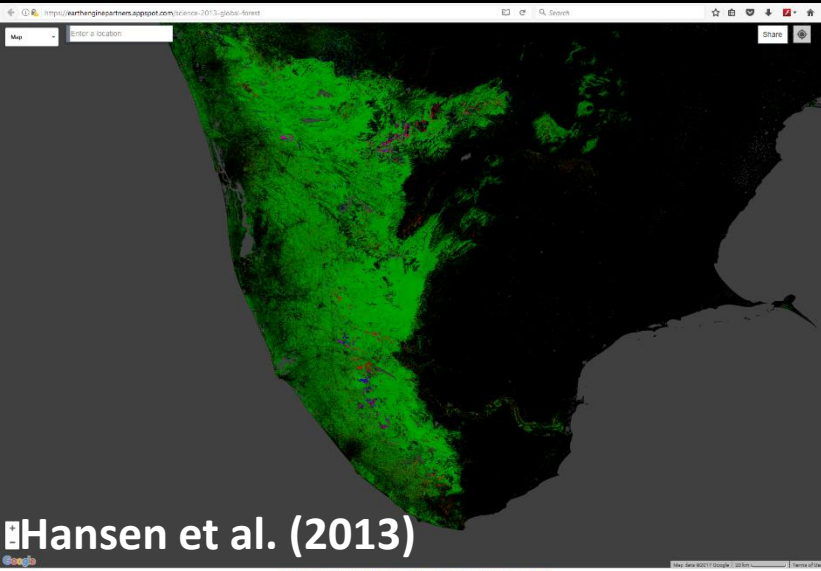
2005



## LEGEND

- |   |                             |   |                              |   |                                |
|---|-----------------------------|---|------------------------------|---|--------------------------------|
|  | Subtropical Wet Hill Forest |  | Cloud                        |  | Bamboo                         |
|  | Semievergreen               |  | Grassland                    |  | Agriculture                    |
|  | Saif                        |  | Current Shifting Cultivation |  | Abandoned Shifting Cultivation |
|  | Subtropical Pine            |  | Water                        |  | Road                           |
|  | Subtropical Mixed Pine      |   |                              |   |                                |
|  | Subtropical Degraded Pine   |   |                              |   |                                |
|  | Moist Mixed Deciduous       |   |                              |   |                                |

# Forest cover change assessment (2000-2010) - An example from South India



# Dynamics of LCLUC - Country Level Studies

- Quantified land-cover and change at country scale using time varying satellite images
  - Bhutan, Bangladesh, India
- Classified maps scene by scene
- Used sub-national scales relevant studies to understand the spatial existence/pattern of land/forest covers
- Used field samples validation data
- LCLUC linking with biophysical and socioeconomic datasets to understand the exact drivers and causes of changes
  - Bangladesh and India

# Improving the existing data - some thoughts

- Mapping algorithms should be designed evaluated using the climate, topography other conditions of the study regions
- Object based image classification - Better than pixel based supervised classification, so results are matching with countries estimated areas
- Use of temporal data improves classification accuracy.
- Land cover change (including forests; not tree cover) improves the misclassified areas
- Share the data with others

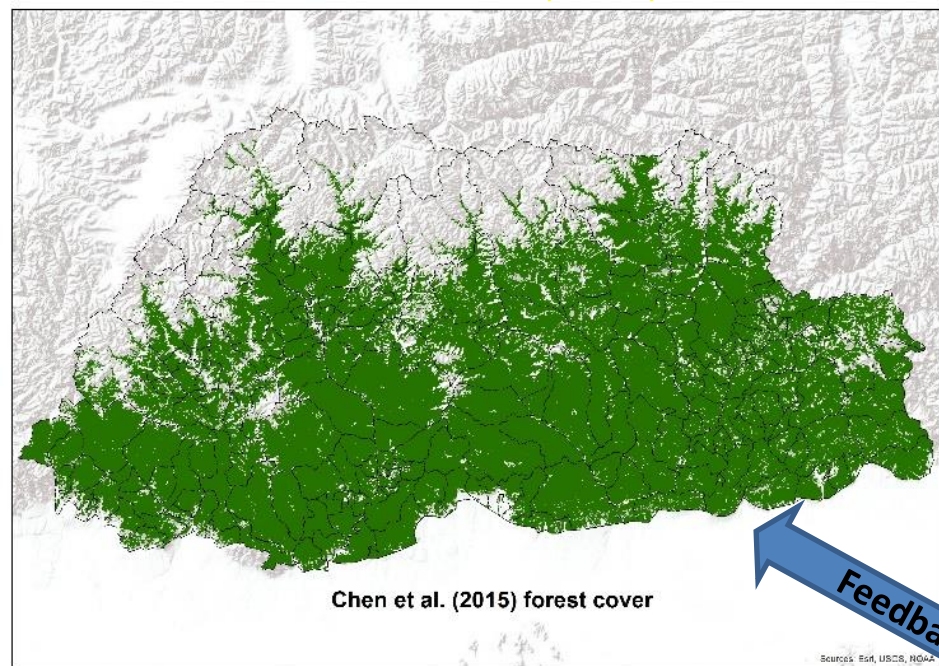
The End

# Extra Slides

# Feedback Mechanism

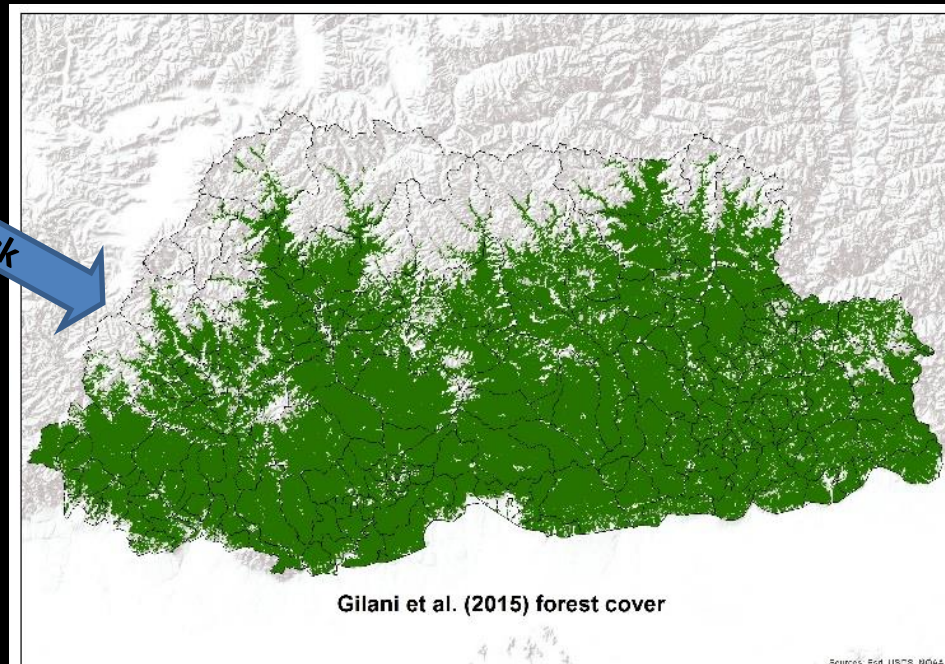
## Bhutan - 2010 Satellite Derived Forest Cover

26,479 km<sup>2</sup> (70%)



- Chen et al. (2015) global scale produced land cover data was provided to ICIMOD (Gilani et al., 2015) for the validation

26,730 km<sup>2</sup> (70%)

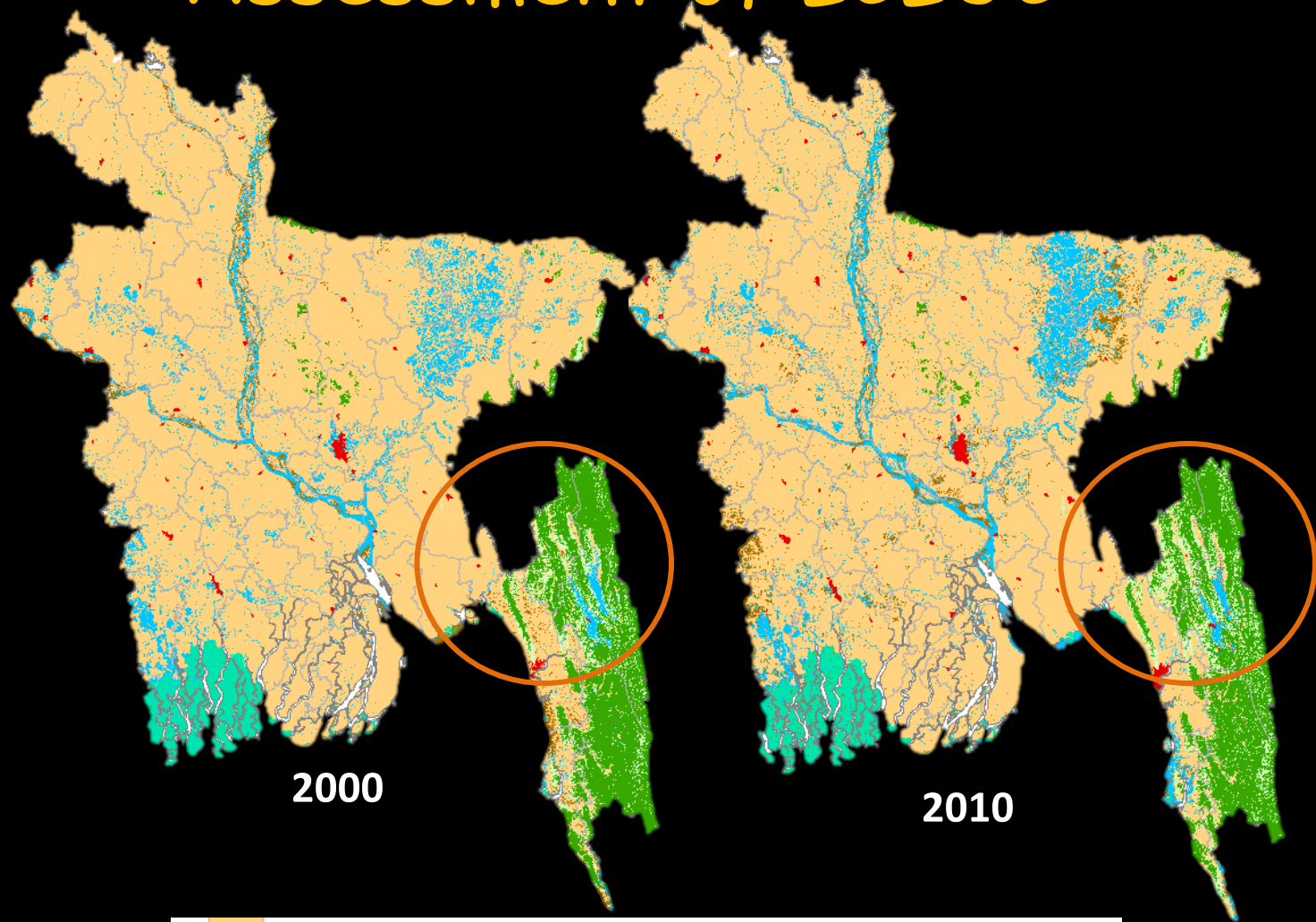


Estimated areas and spatial patterns are matching

- Both (Chen and Gilani) used object based image classification technique



# Bangladesh - A Temporal Change Assessment of LCLUC



2000

2010

